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Employment impacts of renewable energy policies in China: A decomposition analysis based on a CGE modeling framework

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HIGHLIGHTS

- This study quantifies the employment impacts from renewable energy policies in China.
- The net employment impacts are decomposed into direct, indirect and induced effects.
- Most jobs are created in the construction, installation, and manufacturing (CIM) stage.
- Disregarding the negative induced effects leads to overly optimistic conclusions.
- Lump-sum tax is an attractive option to generate employment, or avoid adverse outcomes.

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ABSTRACT

Employment impacts are one of the most important social impacts associated with the development of renewable energy, and are also one of the key concerns for policy makers designing renewable energy policies. Current studies tend to focus on the direct job changes in renewable sectors per se and on the indirect job changes along value chains of renewable energy, therefore depicting a picture of prosperity with large amounts of “green jobs”. However, the induced job changes in other sectors that are not directly in the value chains but are still influenced by electricity price changes and related financial resource transfers have usually been neglected, resulting in an incomplete and potentially biased understanding of this specific category of social impact. By using a computable general equilibrium (CGE) model of China that incorporates detailed renewable power generation technologies and considers labor market imperfections, our study tries to fill this gap and quantifies the full scope of job changes (direct, indirect and induced) brought by renewable energy development in China. Results show that per 1 TW h expansion of solar PV and wind power would create up to 45.1 thousand and 15.8 thousand, respectively, direct and indirect jobs in China. However, the scale of induced job changes is quite significant and may even lead to net job losses in the whole economy in some cases. We have further revealed the sectoral contributors to total job changes. In all, there are no assured conclusions on the occurrence of green jobs when developing renewable energy. The impacts are highly dependent on the species of renewable energy, the financing mechanisms for renewable subsidies, and the scopes of employment impacts. We suggest that full-scope employment impacts should be carefully considered and the detailed supporting policies should be carefully designed by decision makers when promoting renewable energy.

1. Background

The development of renewable energy has featured prominently in China’s policy portfolio for dealing with the challenges of climate change. The total installed capacity of renewable power in China saw booming development in the period of the 12th Five-Year Plan (2010–2015), increasing from 249 GW in 2010 to approximately 504 GW in 2015 [1]. 39.7% and 16.5% of the increase in renewable electricity are attributable to wind power and solar PV, respectively. As pledged in the Nationally Determined Contributions (NDC) under the

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Paris Agreement, the share of non-fossil energy in China's total primary energy consumption will increase to approximately 15% by 2020 and 20% by 2030. To achieve these objectives, China plans to implement several policy instruments to further boost renewable energy deployment in the electric power sector. Feed-in-Tariffs (FITs), which assist in subsidizing renewable technology deployment, are expected to play the most important role among the various policy measures.

The establishment of so-called "green jobs" is an increasing attraction for policymakers to encourage renewable energy development worldwide [2–4]. However, renewable energy deployment will also induce large economic adjustments in competing electric power generation sectors such as coal and natural gas. Direct displacement of these generation sources will cause job losses in the affected sectors, as well as along the supply chains. Induced employment effects, which could be positive or negative, are also possible depending on the relative costs of new renewable technologies compared to conventional generation sources. Since 2006, China has taxed conventional electric power generation in order to subsidize development and deployment of renewable technologies. The tax, which began at 0.001 Yuan/Kwh, has increased to 0.019 Yuan/Kwh in 2016 (~%4 of the sale price of electricity). Employment effects of renewable technology deployment, both positive and negative, should be clearly identified as China moves forward with its electric-power sector transition. It is also important to compare alternative renewable energy policy designs in terms of their overall economic efficiency and employment impacts in order to assist policy makers in their efforts to address both environment and economic development challenges.

The paper is organized as follows. Section 2 reviews the existing literature on the economy-wide employment impacts of renewable technology deployment. Section 3 describes the model, database, and key assumptions used in the study. Section 4 provides a description of the scenarios and presents the main results. Section 5 provides a detailed discussion and concludes.

2. Literature review

Currently, there are three primary approaches to study the employment impacts of renewable energy policies [5,6]: (1) computable general equilibrium (CGE) methods; (2) input-output (I/O) methods; and (3) analytical methods, which generally rely on extensive surveys and focus on a specific technology in a territory (i.e. regional or provincial level). Most existing studies conclude with positive employment impacts, while some cautious researchers still believe in neutral or even negative employment impacts. In fact, different research scopes, methodologies and data sources in existing studies are the major reasons for the divergent understandings on the employment impacts of renewable energy policies. A list of studies that touch upon the employment impacts of renewable energy policies are presented in Table A.1.

From the perspective of research scope, the employment impacts are commonly classified into three categories: direct, indirect and induced [6–10], as is summarized in Table 1. Firstly, direct jobs refer to those created in the renewable sectors to support the increase of generation capacity, while indirect jobs are those created in the value chains of renewable technologies to accommodate the expansion of renewables. As an illustration of the indirect impacts, consider a new wind farm purchasing wind turbines or a new solar PV farm purchasing PV cells. The indirect impacts include not just the first stage in the value chains, but all inter-industry purchases necessary to support the expansion of renewable energy. In traditional I/O terminology, induced impacts refer to changes in household spending resulting from changes in labor income. For example, if labor income in solar PV manufacturing increases, the spending of that labor income on goods and services is an induced effect. In reality, there are additional price induced effects in product and factor markets, which can be captured in CGE models. Perhaps the largest induced effect is the replacement of conventional electric power plants [11], which results from a change in the relative price of conventional electricity and renewable electricity [6,7,10]. Assuming that the policy instrument has the effect of reducing output in conventional electric power, this effect will be unambiguously negative [12]. Among the existing literature, less attention has been paid to the induced impacts due to uncertainty and difficulty of measurement, which may lead to the overly optimistic employment estimates of renewable energy expansion. However, all impacts - direct, indirect and induced - should be taken into consideration to draw a comprehensive picture on the employment impacts of renewable energy.

Different methodologies have their specific advantages and disadvantages to model these direct, indirect and induced employment impacts. These have been well-summarized in previous studies [5,6]. In short, analytical methods have better transparency in the model structure and are commonly used for local or regional studies. However, analytical methods traditionally account only for direct jobs, although some studies [10,11] touch on the indirect employment impacts through linking with life cycle analysis. Both I/O and CGE methods take into account the interactions between renewable technologies and other sectors in the economy, which enables the calculation of direct and indirect employment impacts within a national scope. Although the induced jobs caused by replacement of conventional energy technologies and changes in household income can be evaluated through scenario analysis in I/O models, it is hard to grasp all the "opportunity cost" brought by the development of renewable energy. This is mainly caused by the no-limits assumptions that the supply of production factors (such as capital and labor) is infinite, which has been critically described by some researchers [8,13,14,33] and results in a lack of interactions between prices and quantities [34]. However, opportunity cost is the major mechanism that leads to job losses in the economy. For instance, the development of renewables needs more investment, thus it actually reduces the available capital for other sectors due to scarcity of capital. The ignorance of "opportunity costs" has been criticized by Lesser (2010) [12] as "free-lunch economics". Therefore, it is not

Table 1
Summary of employment impacts.

Employment effects	Cause	Overall impacts	Availability		
			CGE methods	I/O methods	Analytical methods
Direct	Increasing capacity of renewable energy	Positive	√	√	√
Indirect	Increasing demand in value chains	Positive	√	√	√
Induced	Decreasing investment in conventional energy sectors	Negative	√	√	—
	Competition for capital	Negative	√	—	—
	Change in electricity price	Uncertain	√	—	—
	Change in labor wage	Uncertain	√	—	—
	Change in household income	Uncertain	√	√	—

Note: (1) "√" in the table means the effects can be simulated with the specified method, while "—" means the effects can hardly be simulated with that method;
(2) Results in this table are based on a review of relevant literature, including [4,7–32].

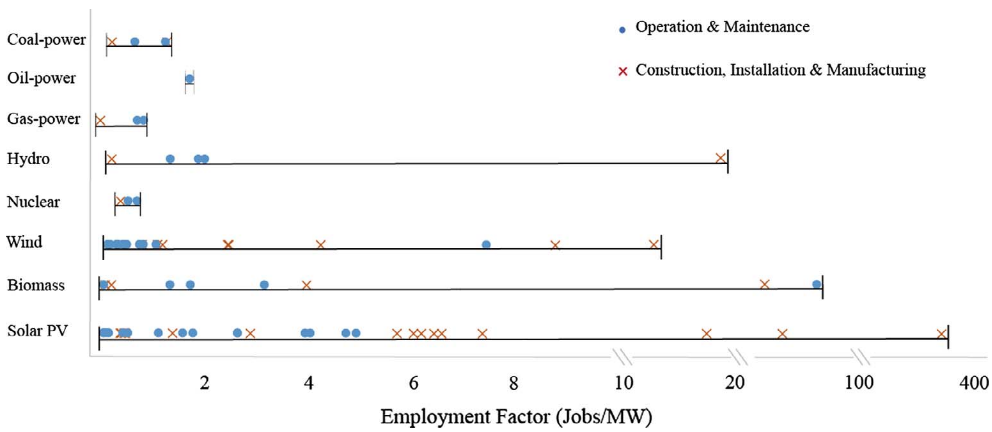

Fig. 1. Summary of employment factors in existing literature [7,10,11,14,16,26,30,31]

surprising to see that most I/O studies have positive conclusions on employment impacts. The CGE model, on the other hand, can take into account most core mechanisms mentioned above, which prevents overstating the employment impacts [15] and presents more comprehensive results for policy makers compared with other methods. However, the biggest challenges for CGE model are the lack of detailed employment data for all sectors in the economy, and the inherent difficulty in establishing such a complex model.

Differences in the scope, quality, geography and source of employment data also contribute to the divergence of assessments on employment impacts. Wei et al. (2010) [16] conduct a detailed review on the employment factors of power technologies in the United States based on literature published from 2001 to 2009, which primarily considered construction, installation & manufacturing (CIM) jobs and operation & maintenance (O&M) jobs. We update this review by adding the employment factors estimated or used in the above literature for different countries around world. As summarized in Fig. 1, most studies find that renewable technologies have much higher employment factors than conventional thermal power technologies, which means the renewable technologies need more workers per unit of electric power generated. However, there is significant variation among the employment factors for renewable technologies.

To quantify the employment impacts of China's renewable policies, this study makes an effort to address the following gaps in the existing literature. First, we establish a comprehensive CGE-based method to analyze the employment impacts of renewable energy, which decomposes the overall impacts into direct, indirect and induced impacts. Imperfect labor market assumptions are implemented in our model rather than the perfectly competitive labor market assumptions in the standard CGE model. With these improvements, renewable policies not only change the allocation of labor factors among sectors but also cause impact on overall employment. Second, our analysis highlights the importance of alternative policy instruments, which are ignored by most relevant studies, for the assessment of employment impacts. Through improving the modeling of renewable electricity technologies and policy instruments, different financial options for feed-in-tariffs are analyzed in our study. Finally, our study helps to overcome a major challenge to the use of CGE models for employment impact assessment by establishing a dataset on sectoral employment and wages in China, which incorporates both the statistical data from a national-scale demographic census [35] and the survey data from independent demographic research [36]. This study, as well as other further research, can be well supported by our dataset.

3. Methodology and data

The employment impacts of China's renewable policies are analyzed using the static version of the China Hybrid Energy and Economic Research (CHEER) model. In the static version, we do not incorporate transitional dynamics processes associated with the renewable policies, but focus on the long-run impacts [20]. The CHEER model is a multi-sector CGE model calibrated to the Chinese economy and was developed as an extension of the Technology-Oriented Dynamic Computable General Equilibrium model for China (TDGE_CHN) developed in Wang et al. (2009) [37]. Compared with other Chinese CGE models, CHEER has more detailed exposition of the production structure, greater technological details in the electricity sector, greater details in the labor market and more options for policy instruments. The CHEER model is calibrated to the 2012 Input-Output table of China [38] and the 2012 energy balance table [39] with 16 aggregated production sectors (Table 2). Since crude oil and natural gas are aggregated as one sector in China's I-O table, the original sector is split according to the relevant cost shares in the GTAP 9 database [40]. The above adjustments make the CHEER model a good tool for quantifying the employment impacts of a variety of renewable policies. A schematic view of the modeling process is presented in Fig. 2.

3.1. Model structure

The CHEER model features a detailed production structure, which is captured by a nested constant elasticity of substitution (CES) production functions. Each sector is assumed to operate under constant returns to scale and cost optimization. The essential inputs of sectoral production include material inputs that generate the input/output table, as well as factor inputs representing value added. The possibilities of substitution among different inputs are controlled by sector-specific elasticities of substitution (σ). The majority of the substitution elasticity parameters (Table 3) are taken from TDGE_CHN, with necessary updates based on the newer study [41].

Production of commodities other than electricity is shown in Fig. 3. Fixed factors, such as land and natural resources, are only required in the agriculture, coal, gas, oil and mining sectors. They are treated as substitutes for other inputs to control short-term sectoral production at the top level of the nested CES structure. At the lower two levels, the energy factors are first combined with the capital-labor aggregation,

Table 2
Sectors in CHEER model.

No.	Sector	Abbr.	No.	Sector	Abbr.
1	Electricity	Elec	9	General Equipment	GenEqp
2	Coal and coking	Coal	10	Transport Equipment	TransEqp
3	Crude oil	Oil	11	Electronic Equipment	ElecEqp
4	Refined Petroleum	RefPet	12	Other Manufacturing	OthMfg
5	Natural gas	Gas	13	Construction	Constr
6	Agriculture	Agri	14	Transport Service	TranspSrv
7	Other mining	Mine	15	Research & Development	R&D
8	Metal Products	MetalPr	16	Other Services	Service

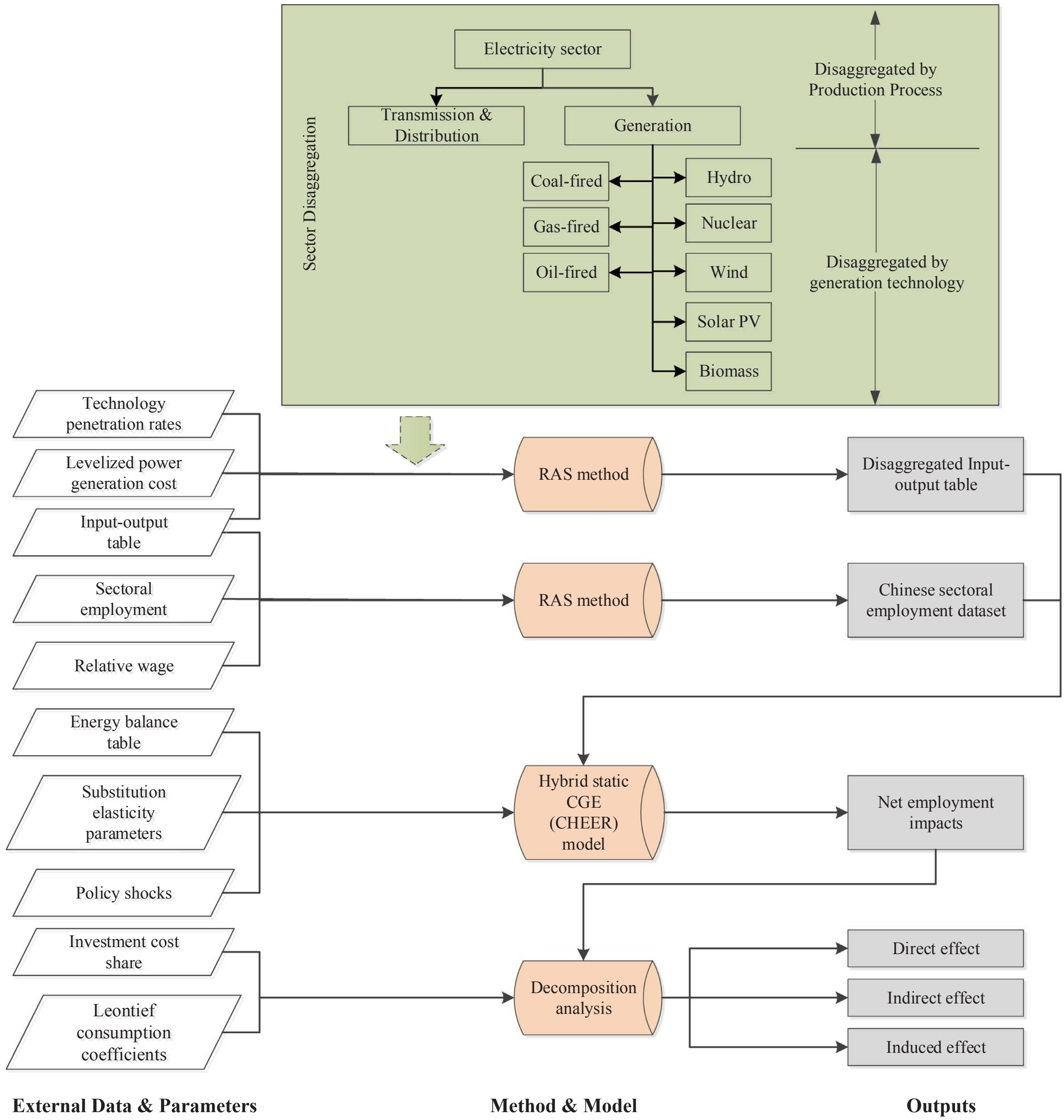

Fig. 2. Schematic view of the modeling process.

Table 3
Core substitution elasticity parameters in the CHEER model.

Parameter	Value	Parameter	Value
σ_{NE}	1	σ_W	1
σ_E	0.5	σ_C	0.25
σ_{KL}	1	σ_{CNE}	0.3
σ_{KLE}	Elec-0.1, Coal/Oil/Petro/Gas-0.8, Agri-0.6, Rest-1	σ_{CE}	0.4
σ_{FF}	Coal/Oil/Gas-0.5, Hydro-0.039, Nuclear- 0.025 Wind-0.25, Solar/Biomass-0.2, Rest-0.3	σ_I	0.25
σ_L	1	σ_{RE}	1.5

Note: The meanings of above substitution elasticity parameters are presented in Figs. 3–5. For example, σ_{KLE} in Fig. 3 means the substitution elasticity between energy composite and capital-labor composite.

and then combined with intermediate inputs. The right-angle connections in the figure represent the fixed proportion input-output relationship (Leontief function), which is a special case of the CES function when σ = 0.

Given the paramount role of the electricity sector for the employment impacts assessment of renewable energy policies, the power production is presented with a more complex nested CES production structure (Fig. 4). The top nest of electricity production is a Leontief combination of power generation and power transmission and distribution. The production in power transmission and distribution is assumed to follow a fixed proportion of labor, capital and intermediate inputs. The production of power generation is competed by eight discrete technologies. Wind and solar PV are imperfect substitutes of baseload generation, due to their intermittency. Baseload generation consists of power from conventional fossil fuels (coal, oil and gas),

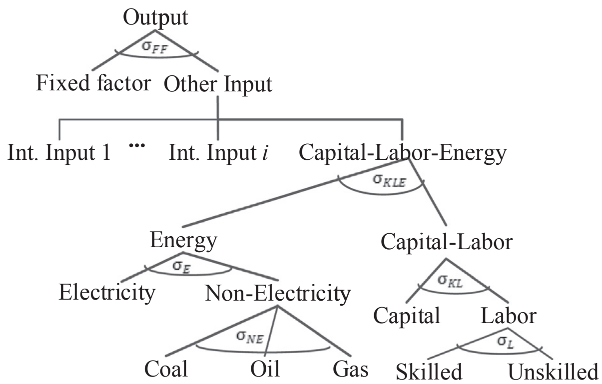

Fig. 3. Nested CES production structure of non-electricity sectors.

nuclear energy, hydropower, and biomass, all of which are with perfect substitutes. In the lower nest, each technology has a similar production structure as non-electricity sectors, while only non-fossil power technologies need fixed factors as essential inputs. The generated power by electricity type in 2012 from the China Electricity Council [42] and levelized costs from the International Energy Agency [43] were used to split the input-output data of electricity sector following the methodology of Peters and Hertel (2016) [44] and Sue Wing (2008) [45] to calibrate the CHEER model.

Consumption in the CHEER model assumes a single representative consumer incorporating household and government. All incomes, including labor compensation, capital remuneration, and tax revenue, are assumed to be distributed to the representative consumer. Disposable income is then allocated between consumption of goods/services and investment. Consumption is modeled using a nested CES consumption function (Fig. 5). The top level assumes a Cobb-Douglas functional form for the tradeoff between consumption goods and investment goods. At the second level, income is allocated to specific consumption and investment commodities assuming constant elasticities of σ_C and σ_I, respectively. At the third level, a further distinction is made between consumption of non-energy and energy commodities. This is intended to represent the idea that substitution among energy commodities is different from substitution among other consumption goods.

The treatment of international trade in the CHEER model follows the commonly used Armington assumption, which allows for import and export differentiation between domestic and international markets [46]. Domestic firms allocate domestic production to domestic and international markets according to a constant elasticity of transformation (CET) function. Imports are substitutable with domestic goods according to a CES function. Export demands and import supplies are set exogenously following the method of Wang et al. (2009) [37].

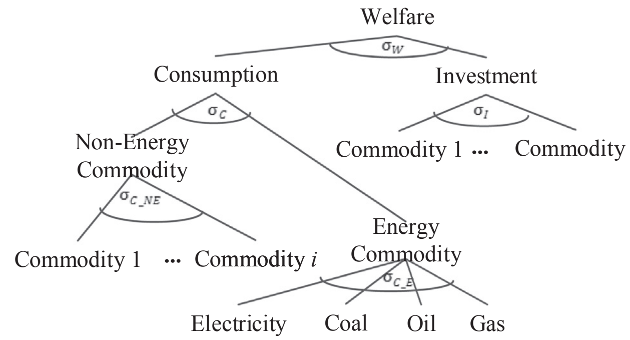

Fig. 5. Nested CES structure of final demand.

As for the production factor in the CHEER model, capital is modeled to be perfectly mobile across sectors. The supply of capital is calibrated to the base year, while the demand of capital varies endogenously to clear the capital market. Due to the paramount role for the evaluation of employment impacts, the labor market is not as straightforward as the capital market and will be elaborated in the next section.

3.2. Imperfect labor market and unemployment

Following neoclassical principles, standard CGE models imply flexible labor wages so that the labor market clears perfectly just as other good or service markets [30]. Consequently, the imperfections of the labor market, which prevent the labor market from clearing and result in involuntary unemployment, are not taken into account. However, in reality, there are two main types of imperfections in the labor market [47,48]: (1) the rigidity of wage adjustment, which means wages cannot be fully adjusted to balance the supply and demand of labor due to minimum wage regulations or union wage negotiations; and (2) the rigidity of labor mobility, which means workers in one sector cannot be transferred to other sectors instantaneously due to the skill gaps or geographic distance. As a result, excluding imperfections in the labor market will lead to bias in the evaluation of employment impacts.

In order to take labor market imperfections into consideration, the CHEER model features a wage curve (Eq. (1)), which is used to describe the relationship between the unemployment rate and real wages in this model. Ur and Ur_0 represent the unemployment rate after and before a shock, respectively, while W/P and W_0/P_0 represent the real wage. β is the core parameter in this equation and reflects the unemployment

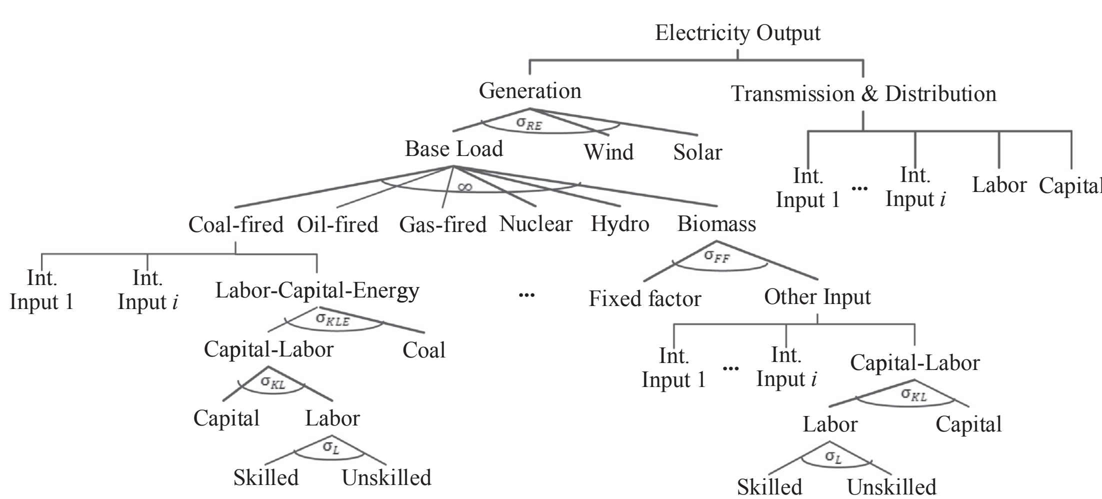

Fig. 4. Nested CES production structure of the electricity sector.

elasticity of the real wage. According to Blanchflower and Oswald (1995) [49], β is approximately −0.1 for any region or country. With the wage curve, the labor market may exhibit frictions with initial unemployment. The CHEER model further considers inter-sectoral wage differentials and imperfect mobility of labor across sectors. Constant elasticity of transformation (CET) functions are used to allocate the total labor supply among sectors.

$$Ur^{\beta} = \frac{W/P}{W_0/P_0} \times Ur_0^{\beta} \tag{1}$$

3.3. Chinese sectoral employment dataset

The objective of this section is to establish a dataset on sectoral employment and wages in China in order to meet the data requirements of the CGE model. The available data sources include: (1) the 6th Chinese population census [35], which was conducted in 2010 and provides the quantity of employment for different labor types in each sector; (2) the Chinese Household Income Project (CHIP) database [36], which is a household survey conducted by Beijing Normal University with 26,527 samples and provides the average wage for each labor type; and (3) the 2012 Chinese Input-Output table [38], which provides the total value of labor compensation in each sector. Based on the above data sources, up to 28 labor types by gender (male/female), region (urban/rural), and educational level (unlettered, elementary school, middle school, high school, junior college, regular college, postgraduate) can be identified. The wage data in 2013 is shown in Table 4.

Theoretically, the relationship between labor compensation and employment quantity is presented in Eq. (2). $LV_{l,i}$ represents the compensation for labor type l in sector i; $LW_{l,i}$ represents the average wage for labor type l in sector i; and$LQ_{l,i}$ represents the quantity of labor type l in sector i.

$$LV_{l,i} = LW_{l,i} \times LQ_{l,i} \tag{2}$$

Only $LQ_{l,i}$ can be directly grasped from the available datasets, while further analysis is needed to estimate the sectoral wage, $LW_{l,i}$, and the sectoral labor compensation $LV_{l,i}$. Following the method used in Perter and Hertel (2016) [44], we define a targeted matrix, $X = \{x_{l,i}\}$, where $x_{l,i}$ represents the targeted compensation for labor type l in sector i. In order to obtain X, we first build an original matrix $A = \{a_{l,i}\}$ based on the available data (LAV_i^0, $LQ_{l,i}^0$, LAW_l^0). LAV_i^0 represents the total value of labor compensation in sector i, which can be obtained from the 2012 Chinese Input-Output table. $LQ_{l,i}^0$ represents the employment quantity of labor type l in sector i, which can be obtained from the 6th population census. LAW_l^0 represents the average wage for labor l, which can be obtained from the 2013 Chinese Household Income Project (CHIP). In this way, the estimation of sectoral wages is converted to an optimization problem to minimize the difference between matrix A and matrix X under several constraints. The definitions of $a_{l,i}$ and $x_{l,i}$ are shown as follows.

$$a_{l,i} = \frac{LAW_l^0}{\sum_l \sum_i (LAW_l^0 \times LQ_{l,i}^0 / \sum_l \sum_i LQ_{l,i}^0)} \times \frac{LAV_i^0}{\sum_i LQ_{l,i}^0} \times LQ_{l,i}^0 \tag{3}$$

$$x_{l,i} = LW_{l,i} \times LQ_{l,i} \tag{4}$$

In the definition of $a_{l,i}$, the first term represents the ratio of the wage rate of labor type l to the average wage of overall labor, while the second item represents the average wage in sector i. It is a key assumption that the ratio of wage rates of specific labor types to the overall labor wage is constant for all sectors. In order to avoid data inconsistencies due to the different sources of data, the survey data are only used to calculate the relative wage rates rather than the absolute wage levels. The optimization problem can be represented as followed:

$$Min_{x_{l,i}} \sum_l \sum_i x_{l,i} \ln \frac{x_{l,i}}{a_{l,i}} \tag{5}$$

$$S.\ t.\ \sum_l x_{l,i} = LAV_i^0 \tag{6}$$

The objective function is built following the RAS method, which is a well-known method for data reconciliation. The constraint is used to keep the sectoral labor compensation consistent with the Input-Output table. Through solving the optimization problem, we can obtain the targeted matrix X with sectoral labor compensation as well as balanced sectoral employment and sectoral wage for each labor type. In order to simplify the analysis, the 28 labor types are then aggregated into two groups, skilled and unskilled, based on education level in this study.

In order to distinguish the characteristics of different power generation technologies, the employment data for the electricity sector is further disaggregated. Similarly, we first calculate the relative labor intensity based on the direct employment factors from Cai et al (2011) [7] and the share of labor skills based on the GTAP-Power data (Peters and Hertel, 2016) [44]. The quantity of employment corresponding to each technology can be then estimated using the average wages in the electricity sector. The above data are presented in Tables A.2 and A.3.

3.4. Measurement of employment impacts

Although the precise definitions and assumptions of the measurements associated with employment impacts vary in the literature, sectoral output value (Y_i, in billion Yuan) and labor intensity (LI_i, in thousand jobs/billion Yuan) are two core factors determining sectoral labor demand (LD_i, in thousand jobs), as shown in Eq. (7). In this method, both sectoral output value and labor intensity would change as response to the development of renewable power and thus affect the total labor demand.

Table 4
2013 average wages for different labor types in China.

No.	Gender	Region	Education	Wage (Yuan)	No.	Gender	Region	Education	Wage (Yuan)
L1	Male	Urban	Unlettered	23431	L15	Female	Urban	Unlettered	14356
L2			Elementary school	26275	L16			Elementary school	18451
L3			Middle school	34098	L17			Middle school	23097
L4			High school	39976	L18			High school	31570
L5			Junior college	47648	L19			Junior college	36160
L6			Regular college	57187	L20			Regular college	46625
L7			Postgraduate	93353	L21			Postgraduate	68316
L8		Rural	Unlettered	17891	L22		Rural	Unlettered	12910
L9			Elementary school	21849	L23			Elementary school	16950
L10			Middle school	28150	L24			Middle school	20751
L11			High school	30022	L25			High school	23483
L12			Junior college	35971	L26			Junior college	29295
L13			Regular college	38878	L27			Regular college	33715
L14			Postgraduate	47189	L28			Postgraduate	28733

$$LD_i = Y_i \times LI_i \tag{7}$$

In order to decompose the overall employment impacts, additional assumptions are used here. On the one side, direct and indirect employment effects are calculated following the method in the I/O literature [7–9], which assume a linear economy and fixed labor intensity. On the other side, induced effects are distinguished subsequently based on the results of the CGE simulation, which takes into account residual effects other than direct and indirect effects, including changes in both sectoral outputs and labor intensities due to general equilibrium interactions.

In the calculation process, direct and indirect effects are distinguished by sectors in which jobs are created. Direct effect refers to jobs created inside the target renewable sector (i.e. wind power or solar PV), while indirect effect refers to jobs created outside the target renewable sector. First, the direct effect (EI^{direct}) is calculated by multiplying the change of output value from specific renewable technology ($\Delta Y_{renewable}$) and its initial labor intensity ($\overline{LI}_{renewable}$), as is shown in Eq. (8). Matched with the life cycle of renewable power plant, direct effect mainly includes jobs created by the operation activities.

$$EI^{direct} = \Delta Y_{renewable} \times \overline{LI}_{renewable} \tag{8}$$

Second, the indirect effect ($EI^{indirect}$) is calculated through Equations (9)–(11). Two components are included in the calculation of indirect effect, which are matched with jobs created by the construction, installation, and manufacturing (CIM), and maintenance of renewable power plant, respectively. CIM jobs are calculated by multiplying the change of installed capacity ($\Delta Capacity_{renewable}$, in GW) associated with each renewable expansion scenario, the unit investment cost ($InvCost_{renewable}$, in billion Yuan/GW), the demand share of investment goods for sector i for each renewable technology ($InvCost_{i,renewable}$) and the labor intensity in sector i ($\overline{LI}_i$). The conversion ratios from generated power to installed capacity are calculated based on official Chinese statistical data [42], while the data for investment cost and sectoral share of wind power and solar PV are taken from Dai et al (2016) [50] (Table 5). Maintenance jobs are calculated by multiplying the change of output value from certain renewable technology ($\Delta Y_{renewable}$), Leontief consumption coefficients ($LCC_{i,renewable}$) and the labor intensity in sector i ($\overline{LI}_i$). Leontief consumption coefficients, representing the consumption of commodities from sector i to support each unit of output in the targeted renewable sector, can be calculated from the I-O table.

$$EI^{indirect} = \sum_i (CIM_i + Maintenance_i). \tag{9}$$

$$CIM_i = \Delta Capacity_{renewable} \times InvCost_{renewable} \times InvShr_{i,renewable} \times \overline{LI}_i \tag{10}$$

$$Maintenance_i = \Delta Y_{renewable} \times LCC_{i,renewable} \times \overline{LI}_i \tag{11}$$

Both the direct and indirect effects reflect the impacts of renewable policies on employment assuming a fixed production technology and no price effects. In contrast, the net employment impacts, calculated through the CGE simulation, take into account important price and income effects associated with the renewable energy policies. As a result, the value of induced effects ($EI^{induced}$) is calculated by netting out the direct and indirect effects described above from the total employment impacts (EI^{net}) generated by the CGE model (Eq. (12)).

$$EI^{induced} = EI^{net} - EI^{direct} - EI^{indirect} \tag{12}$$

Table 6
Scenario description.

Scenarios	Financial Instrument
Electricity Consumption Fee (ECF)	FIT financed by electricity fees
Lump-Sum Tax (LST)	FIT financed by lump-sum tax

4. Scenarios and results

4.1. Scenario definition

We develop a reference scenario and two renewable electricity policy scenarios in this study (Table 6). The reference scenario is calibrated to 2012 without any additional policy shocks as a baseline for the analysis. In the reference scenario, power generated from wind and solar sources are 103.0 TW h and 0.36 TW h, respectively. Then, policy simulations are conducted to expand the power generation from wind and solar PV in policy scenarios through two different financial instruments, which include Feed-In-Tariffs (FITs) financed by (i) an additional electricity consumption fee (ECF) and (ii) a lump-sum tax (LST). Solar PV and wind expansions are each modeled independently. Since the model used here is static, policy simulations show counterfactual results if wind power or solar PV expand in China and the rest economic system run in the same method as it does in 2012.

ECF is the current renewable electricity financing mechanism used in China. It is modeled as a commodity tax and is levied directly on electric power consumers, including enterprises and households, in the CHEER model. Meanwhile, LST represents another widely discussed mechanism to finance the cost [18] or recycling the revenue [51,52] of energy and emission mitigation policies. It is modeled as an income tax on the representative consumer in the CHEER model. In the simulation, generation of wind power or solar PV is shocked to increase from 1 TW h to 15 TW h, while ECF and LST are determined endogenously.

4.2. Results

This section reports results for all renewable expansion scenarios. Results are presented as average full time employment changes from the reference scenario per unit expansion of power generated from wind power or solar PV (thousand jobs/TW h). Unless otherwise stated, the expansion targets for wind power and solar PV are set as 1 TW h in policy scenarios.

4.2.1. Direct and indirect employment effects

The direct and indirect employment effects for wind and solar power expansion are all positive due to the growth in these industries. These effects can be illustrated at three stages in the life cycle of wind and solar PV technologies (Fig. 6). The CIM phase illustrates the indirect jobs created through capacity investments, the operation phase

Table 5
Investment cost for wind power and solar PV.

	Capacity factor (TW h/GW)	Investment cost (Billion Yuan/GW)	Investment demand share (%)							
			MetalPr	TransEqp	GenEqp	ElecEqp	Constr	TranspSrv	R&D	Service
Wind Power	1.667	9	5	5	38	5	15	12	8	12
Solar PV	1.056	20	3		40	12	13	8	10	14

Note: (1) Conversion ratios calculated by dividing the total generated power by the installed capacity of wind power and solar PV in 2012, respectively. Higher conversion ratio means higher conversion efficiency.
(2) Data of investment cost and demand share are taken from Dai et al (2016) [50].

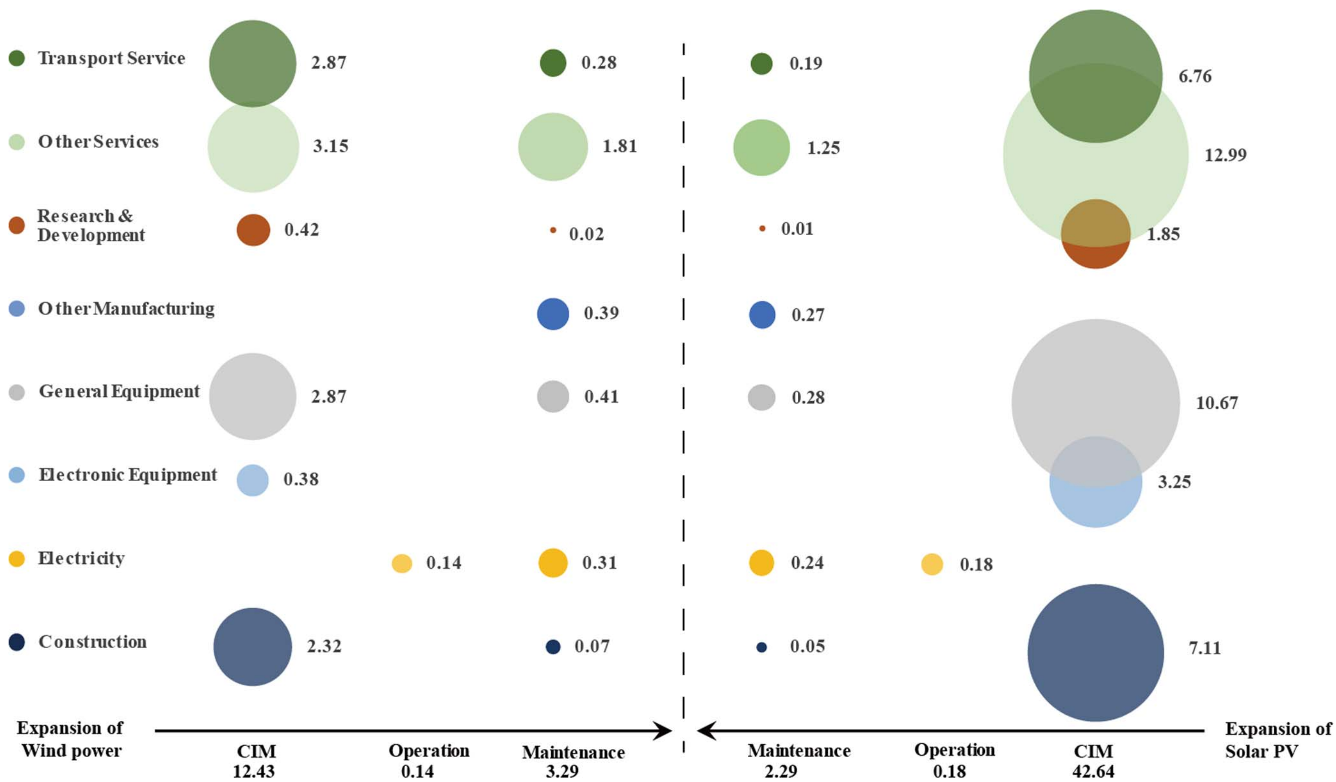

Fig. 6. Employment impacts (Thousand Jobs/TW h) in CIM, operation and maintenance stages of wind power and solar PV in China. The size of each bubble is consistent to jobs created in the corresponding sector. The numbers at the bottom of this figure stand for the total jobs created in the corresponding stage.

includes the direct jobs necessary to manage a facilities daily operations, and the maintenance phase includes the indirect jobs required to support occasional maintenance activities. Operations-phase employment is the smallest component of the direct and indirect workforce for wind and solar PV, accounting for 140 jobs/TW h and 180 jobs/TW h, respectively. Comparatively, coal power generation technology has a much higher labor intensity (481 jobs per TW h), which is 3.5 times that of wind power and 2.7 times that of solar PV. As mentioned previously, one possible reason for this discrepancy is that wind and solar technologies are more technically concentrated and have higher value-added than coal power generation technology. Although expansion of wind power and solar PV will create direct jobs to operate the new capacity, the transition towards renewable power, considering the major role of coal power in China, will lead to a decrease in the average labor intensity in the electricity sector.

From the perspective of indirect employment effect, jobs are created along the value chains to accommodate the CIM and maintenance requirements of renewable power, resulting in 15.72 thousand jobs per TW h for wind power and 44.93 thousand jobs per TW h for solar PV. There are divergences with respect to the two components of indirect jobs. In the CIM stage, due to much higher unit investment cost and relative low conversion efficiency, the indirect jobs created by solar PV (42,640 jobs/TW h) are 3.43 times as large as that created by wind power (12,430 jobs/TW h). In the maintenance stage, wind power, in turn, creates more jobs along the value chain (3290 jobs/TW h) than solar PV (2290 jobs/TW h). The reason is that, based on the levelized cost data (IEA, 2015), only 12.7% of the solar PV generation costs (19.5 USD/MW h) are spent on operation and maintenance process, as opposed to 30.5% (21.9 USD/MW h) for wind power. Comparatively, jobs created in the maintenance stage are much lower than those created in the CIM stage for both wind power and solar PV.

The distribution of indirect jobs among sectors is similar for wind power and solar PV. For wind power, 31.6% of the indirect jobs are created in the service sector, which makes it the most affected sector in both the CIM stage and maintenance stage. The labor intensity in the service sector (4900 workers/billion yuan) ranks only after the agriculture sector (37.6 thousand workers/billion yuan), which is the primary reason why service activities account for a higher share with respect to job creation than its share in the cost structure of wind power. Comparatively, only 20.8% of the indirect jobs are created in the general equipment sector due to a relative lower labor intensity (1400 workers/billion yuan) though 38% of the total investment cost is spent to purchase necessary machinery in the CIM stage (Table 5). Another 20.0% and 15.2% of the total indirect jobs, which are mainly created in the CIM stage, are allocated to transport and construction sectors, respectively. The rest of indirect jobs are in R&D (2.8%), other manufacture (2.5%), electronic equipment (2.5%), electricity (2.0%), and transport equipment (1.7%).

4.2.2. Induced employment effect

Since the economy is assumed to be in equilibrium in the reference scenario, more subsidies are required to finance the expansion of wind power and solar PV. Since the induced effect is defined as the residual effect other than direct and indirect effects, it is a combination of general equilibrium interactions after policy shocks, as discussed in Section 2. In order to elaborate the underlying mechanism, we mainly focus on three aspects.

First, the electricity price is most directly affected by policy shocks and there are significant differences between two financial mechanisms, as is shown in Fig. 7. In ECF scenarios, where the costs for renewable subsidies are paid directly by electricity consumers, a higher subsidy rate will result in a higher price for consumers. The simulation results show the electricity price is 0.04% and 0.07% higher than the reference level in cases that power generation from wind power and solar PV increase by 1 TW h, respectively. In comparison, since the costs for renewable subsidies are shared by the whole economy in LST scenarios, a higher subsidy rate will result in a lower electricity price for consumers. The simulation results show the electricity price is 0.05%

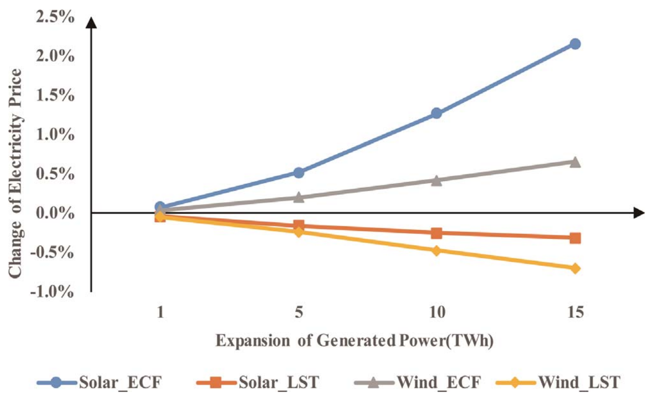

Fig. 7. Change of electricity price associated with the expansion of renewable power generation.

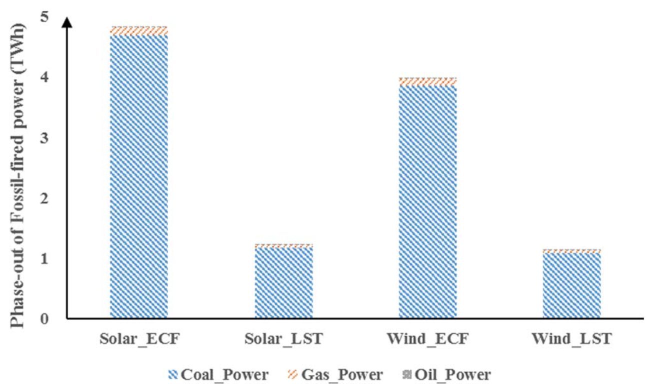

Fig. 8. Phase-out of fossil-fired power in the case that power generation from wind power or solar PV increase by 1 TW h.

Table 7
Change of sectoral activity level compared with reference due to induced effect.

Sectors	Wind_ECF	Wind_LST	Solar_ECF	Solar_LST
Coal	−0.034%	−0.001%	−0.045%	−0.003%
GenEqp	−0.032%	−0.024%	−0.192%	−0.181%
Gas	−0.024%	−0.001%	−0.042%	−0.013%
Service	−0.015%	−0.013%	−0.088%	−0.085%
TranspSrv	−0.014%	−0.011%	−0.088%	−0.083%
R&D	−0.013%	−0.009%	−0.070%	−0.065%
Constr	−0.012%	−0.007%	−0.043%	−0.036%
Oil	−0.011%	0.012%	−0.021%	0.010%
OthMfg	−0.009%	−0.004%	−0.047%	−0.041%
TransEqp	−0.008%	−0.004%	−0.025%	−0.019%
RefPet	−0.004%	0.007%	−0.008%	0.007%
Agri	−0.003%	0.000%	−0.007%	−0.004%
Mine	−0.002%	0.010%	−0.013%	0.003%
ElecEqp	−0.002%	0.002%	0.002%	0.007%
MetalPr	0.000%	0.007%	−0.001%	0.009%

Table 8
Components of net employment impacts (Thousand Jobs/TW h).

Employment Impacts	Solar PV		Wind Power	
	ECF Scenario	LST Scenario	ECF Scenario	LST Scenario
Net	15.0	34.1	−0.8	13.6
Direct	0.2	0.2	0.1	0.1
Indirect	44.9	44.9	15.7	15.7
Induced	−30.1	−11.0	−16.7	−2.2

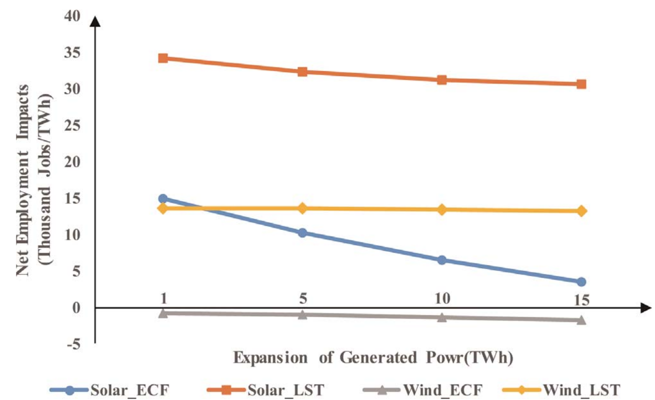

Fig. 9. Net employment impacts associated with the expansion of renewable power generation.

and 0.04% below the reference level in cases that the power generation from wind power and solar PV increase by 1 TW h, respectively.

Second, the expansion of renewable power will lead to the phase-out of fossil-fired power, which is determined endogenously by CGE model in this study. As is shown in Fig. 8, the phase-out of fossil-fired power is not a simple one-to-one replacement. Especially in ECF scenarios, the increase of electricity price lead to a decrease in the total demand of electricity and thus the fossil-fired power will phase out more than the expansion of wind power or solar PV. As a result, if wind power and solar PV expand by 1 TW h, 210 and 320 jobs will be lost in other power generation technologies, respectively. In LST scenarios, the negative induced effect in electricity sector is reduced to 120 jobs/TW h and 190 jobs/TW h for wind power and solar PV, respectively, due to more moderate phase-out of fossil-fired power.

Last, the induced effect will affect the activity level of other sectors and result in change in total employment. In ECF scenarios, increasing electricity price pushes the upward sloping supply curves of other production sectors leftwards and reduce the activity level, as is shown in Table 7. For wind power, the induced job losses can be as large as 16,660 jobs/TW h in all sectors. In LST scenarios, the underlying mechanism is not as straightforward as that in the ECF scenarios. Although a lower electricity price will encourage sectoral production, the cost for renewable subsidies burdened by the representative consumer will reduce the final demand and exert an opposite effect on sectoral production. So the induced effect is determined by the relative strength of these two effects. The simulation results show that the negative induced employment effects are significantly reduced in all sectors compared with the ECF scenarios. For wind power, the induced job losses in all sectors including electricity are reduced to 2250 jobs/TW h, which is 79.6% less than that in the ECF scenario.

4.2.3. Net employment impacts

The net employment effect of wind power and solar PV is the sum of the direct, indirect and induced employment effects (Table 8). Based on the above results, the direct and indirect employment effects are positive in all scenarios but will be partly or totally offset by the negative induced employment effects. In the ECF scenarios, the net effect of the expansion of wind power per TW h will result in 800 fewer job relative to the reference scenario, while 14,990 net jobs/TW h will be created, relative to the reference scenario, due to an expansion of solar PV. Comparatively, the induced job losses will be significantly reduced if the financial mechanism is converted from an electricity consumption fee in the ECF scenarios to a lump-sum tax in the LST scenarios. The transformation of financial mechanism will lead to net job gains in the whole economy for both wind power (13,620 jobs/TW h) and solar PV (34,090 jobs/TW h).

Additionally, the simulation results also show that the net employment impacts, measured in thousand jobs per TW h, decrease as

Table A1
Review of existing literature.

Authors	Region	Policies Studied	Method	Employment Impacts
Kuster et al. (2007) [17]	Global	Capital subsidies on renewable energy sources	CGE	Negative
Allan et al. (2008) [19]	Scotland	Installation of marine energy capacity	CGE & I/O	Positive
Boehringer et al. (2012) [20]	Canada	Renewable feed-in tariff	CGE	Negative
Boehringer et al. (2013) [18]	German	Subsidies to power production from renewable energy	Theoretical model & CGE	Positive/Negative
Cansino et al. (2013) [21]	Spain	Increase in the production capacity of installed biofuel plants	CGE	Positive
Rivers et al. (2013) [22]	US	Tax on fossil fuels/subsidy on renewable power	Theoretical model & CGE	Positive/Negative
Allan et al. (2014) [15]	Scotland	Installation of marine energy capacity	CGE & I/O	Positive
Cansino et al. (2014) [23]	Spain	Increase in the production capacity of installed solar parks	CGE	Positive
Lehr et al. (2008) [24]	Germany	Renewable support policy	I/O	Positive
Neuwahl et al. (2008) [25]	EU	Biofuels penetration scenarios	I/O	Neutral
Caldes et al. (2009) [13]	Spain	Constructing and operating solar thermal plants	I/O	Positive
Cai et al. (2011) [7]	China	Development of renewable energy	I/O	Positive/Negative
Tourkolias et al. (2011) [26]	Greece	Exploitation of renewable energy sources in the power sector	I/O	Positive
Oliveira et al. (2013) [8]	Portugal	Deployment of electricity from renewable energy sources	I/O	Positive
Wang et al. (2013) [9]	China	Clean Development Mechanism (CDM) projects	I/O	Positive/Negative
Cai et al. (2014) [27]	China	Development of renewable energy	I/O	Positive/Negative
Behrens et al. (2016) [4]	Portugal	Feed-in tariff	I/O	Positive
Guenther-Luebbers et al. (2016) [28]	Germany	Increase in biogas production	I/O & system dynamics model	Positive
Markandya et al. (2016) [48]	EU	Low-carbon transformation	I/O	Positive
Moreno et al. (2008) [49]	Spain	Renewable energy	Analytical	Positive
Llera et al. (2010) [50]	Spain	Renewable energy	Analytical	Positive
Wei et al. (2010) [18]	US	Clean energy industry	Analytical	Positive
Grossmann et al. (2012) [51]	Global	Large-scale photovoltaics generation	Analytical	Positive
Llera et al. (2013) [11]	Spanish & German	Deployment of Solar PV	Analytical	Positive
Ortega et al. (2015) [14]	EU	Renewable electricity deployment	Analytical	Positive
Sooriyaarachchi et al. (2015) [10]	Germany, Spain, et al.	Development and deployment of renewable energy and energy efficiency technologies	Analytical	Positive

Note: (1) more than one methodologies are used in some studies;
(2) a theoretical model refers to an abstract CGE model that can be solved analytically;

Table A2
Chinese sectoral employment and wage in 2012.

Sector	Skilled Labor		Unskilled Labor	
	Employment Quantity (Thousand People)	Annual Wage (Yuan/ Person)	Employment Quantity (Thousand People)	Annual Wage (Yuan/ Person)
Elec	1450.2	112761.8	2480.5	79323.4
Coal	573.1	173625.5	4576.8	115713.0
RefPet	419.1	165925.4	695.6	117170.8
Roil	222.1	179664.7	347.9	125579.9
Gas	148.0	49996.2	346.8	34715.4
Agri	7081.4	26637.9	329439.3	15514.2
Mine	232.4	206741.7	2118.0	132384.3
OthMfg	6716.2	78412.7	71036.7	38189.1
MetalPr	1375.6	125320.1	10205.2	71378.4
GenEqp	2933.6	88009.3	14408.5	56275.6
TransEqp	1267.3	118422.8	5293.7	80729.5
ElecEqp	1701.2	101303.4	7554.1	55198.8
Constr	2583.8	95059.5	37282.3	53659.6
TranspSrv	2550.5	72058.6	22222.6	36499.8
R&D	1607.1	233483.7	832.3	145230.1
Service	54362.4	90586.4	126565.3	35587.5

Table A3
Employment data by electricity technology in 2012.

Unit: Thousand People	T_D	Coal_Power	Gas_Power	Oil_Power	Nuclear	Hydro	Wind	Solar	Biomass
Skilled Labor	526.5	659.2	11.3	1.3	8.1	224.6	5.2	0.2	13.7
Unskilled Labor	900.6	1127.6	19.3	2.2	13.9	384.1	9.0	0.4	23.4

renewable electricity expands for all simulation scenarios (Fig. 9). The declining employment impacts for solar PV are more sensitive to the scale of expansion than those of wind power, while the sensitivities for both solar PV and wind power are much lower in LST scenario than those in ECF scenario. This result suggests that the ability to create jobs through developing renewable power is not unlimited and as renewable expansion becomes more aggressive higher subsidies will be required to offset an increasing marginal cost of generation. This in turn will create larger distortions in the economy and increase the negative induced employment effects.

5. Discussions and conclusions

5.1. Are "green jobs" created along with the development of renewable power in China?

The results presented in this study show there are no certain conclusions on the net creation of "green jobs" along with the development of renewable power. The conclusions are highly dependent on the type of renewable energy, the financing mechanisms for renewable subsidies, and the scope of employment impacts.

The most positive conclusion can be drawn in the scope that accounts for all the direct and indirect employment effects, including jobs created in the CIM, operation and maintenance stage. Within this scope, solar PV can create many more jobs than wind power, especially in the CIM stage. However, one of the most straightforward challenge to this assumption is that the total fund required to subside the renewable projects in China, estimated based on the data from Ministry of Finance of China, increases from approximately 15.7 billion yuan in 2010 to more than 100 billion yuan in 2016, which is nearly 0.1% of China's GDP. When the scarcity of production factors, the interactions between sectors, and the costs of renewable subsidies are taken into account, as is the scope of overall jobs, the employment impacts of renewable power turn out to be much more conservative, although still positive. In most scenarios, the direct and indirect jobs creation is partly offset by the negative induced impacts caused by the general equilibrium interactions such as an increase in electricity price and the increase in tax burden.

Among all the scopes, jobs created in the CIM stage play a dominant role for the conclusions on employment impacts. The temporary nature of CIM jobs are noted in many studies, while the operation and maintenance jobs are considered more stable [6,10,11]. Since the subsidies through FIT are anchored to power generation, the induced effects will also stay in action throughout the whole life cycle of renewable projects. As a result, in the most conservative scope which only focuses on the stable jobs and excludes CIM jobs, the net employment effects are negative in most scenarios. In this scope, wind power has advantages to create more jobs mainly due to smaller induced job losses, regardless of which financial mechanism is used. It is consistent with the much lower feed-in-tariff necessary for wind power in China (0.44–0.60 Yuan/KWh in 2016) relative to that for solar PV (0.80–0.98 Yuan/KW h).

There are two important implications behind this discussion. First, policy-makers should be aware that negative induced employment effects are likely to offset some of the direct and indirect positive employment effects of renewable energy expansion. Discounting or disregarding these effects will lead to overly optimistic conclusions and policies. On the other hand, the distinction between the nature of different employment effects should be clearly made especially for the policy makers who are more interested in creating stable jobs.

5.2. How to finance the renewable power? electricity consumption fee vs. Lump sum tax

As mentioned above, additional electricity consumption fees are the current financial instrument to fund subsidies for renewable technologies in China. This follows the "polluter pays principle", which partly internalizes the externalities caused by pollution from electricity consumption. However, the analysis in this study shows that the electricity consumption fee is not the most efficient financial mechanism in terms of generating employment, or avoiding adverse employment outcomes. In contrast, the negative employment impacts in all the adversely affected sectors are significantly reduced if the financial mechanism is converted to the lump-sum tax. Additionally, the advantages of lump-sum tax as the financial instrument for renewable power are increasingly important when there is large-scale expansion (beyond 1 TW h) of wind power and solar PV.

As a consequence, the lump-sum tax should be an attractive option for policy makers especially when there is high and persistent unemployment or when there are aggressive plans for the expansion of renewable energy. However, policy makers should be cautious about regarding the development of renewable energy as a job creation engine, considering the tradeoff between environmental efficiency and job creation.

5.3. Strengths and limitations

This study contributes to the literature by analyzing the employment impacts of renewable expansion in China. Direct, indirect, and induced employment impacts are clearly decomposed and quantified in the novel CGE-based framework. The results stress that the induced employment effects, which present a challenge to study using analytical and I/O methods, are significant in magnitude and opposite in direction relative to the direct and indirect employment effects and should not be ignored in the policymaking process.

This study has several limitations. First, we evaluate the employment impacts of wind power and solar PV in China, separately. Yet, an energy portfolio targeted evaluation could present more accurate results on the employment impacts of renewable policies, considering the synergy and tradeoff between different technologies. Second, since this study is conducted with a static model, we do not incorporate potentially important dynamic elements of the economic environment, especially the technological progress. Large-scale investment in renewable technologies could result in significant learning effects and reduce incremental investment costs over time [50]. This effect could reduce the jobs created in the CIM stage, as well as reduce induced job losses since subsidy payments would be lower. Furthermore, we reveal the potential trade-offs between the "polluter pays principle" and job creation. Future work is needed to study the design of renewable policies under multi-dimension targets.

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Appendix

See Tables A1–A3.

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